Does Software Design Complexity Affect Maintenance Effort?

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Abstract

The design complexity of a software system may be characterized within a refinement level (e.g., data flow among modules), or between refinement levels (e.g., traceability between the specification and the design). We analyzed an existing set of data from NASA's Software Engineering Laboratory to test whether changing software modules with high design complexity requires more personnel effort than changing modules with low design complexity. By analyzing variables singly, we identified strong correlations between software design complexity and change effort for error corrections performed during the maintenance phase. By analyzing variables in combination, we found patterns which identify modules in which error corrections were costly to perform during the acceptance test phase.

1 Introduction

Software systems seldom remain unchanged after their initial development and delivery. A system may be extended to fulfill new specifications or may be repaired to remove faults. These changes, as well as many others, are performed during a period of time called the maintenance phase.

Some authors see software design complexity as a highly important factor affecting the costs of software development and maintenance [Rom87, CA88]. We performed a study to test the hypothesis that changes to modules with high software design complexity require more personnel effort than changes to modules with low complexity. We define software design complexity in terms of several different factors, and test the hypothesis by investigating how the complexity factors affect the costs of changing the software.

If we can determine the impact of the complexity factors on maintenance effort, we can develop guidelines which will help reduce the costs of maintenance by recognizing troublesome situations early. In response to these situations, the developers may decide to reduce the software design complexity of the systems themselves, to develop tools that support maintenance of complex modules, to write documentation that helps the developers manage the complexity better, or simply to re-allocate resources to reflect the situation. Our results might even be used to justify an expensive, controlled experiment to test the hypothesis more rigorously.

In the case study presented here, we used an existing set of data to investigate the impact of software design complexity on the effort required to implement changes during the acceptance test and maintenance phases. We studied two FORTRAN systems from NASA's Software Engineering Laboratory (SEL). The independent variables of the design complexity included a mapping to the specification, global data bindings, and control flow relationships. The dependent variables on maintainability were gathered by the SEL and include the necessary effort for isolating and implementing changes.

This paper extends work first presented in [Epp94]. Section 2 gives the design of the case study, Section 3 discusses our complexity and effort metrics, and Section 4 explains the context of the study. Section 5 states the results for the maintenance and acceptance

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test data, and sketches related work. Finally, Section 6 summarizes lessons for the SEL, the researchers, and the software-engineering community.

2 Designing the Study

This study, which was motivated in part by [Rom87], began by refining the original hypothesis into two, closely related hypotheses:

Hypothesis 1: Changing modules that implement many specifications requires more effort than changing modules that implement few specifications.

Hypothesis 2: Changing modules that are tightly coupled to each other via data and control-flow relationships requires more effort than changing modules that are loosely coupled to each other.

2.1 Design

The case study to test our hypotheses was designed using the Goal/Question/Metric Paradigm [BW84, BR88]. Our G/Q/M goal was to analyze two FORTRAN systems for the purpose of characterizing them with respect to the influence of design complexity on the maintainability of modules, from the point of view of the researchers within the context of the SEL. We analyzed vertical design complexity (traceability to specifications) and horizontal design complexity (coupling among modules). We defined maintainability in terms of change isolation effort, change implementation effort, and the number of modules changed (locality of the change). Using these definitions, we refined the goal into a set of questions, and in turn refined the questions into a set of metrics. Figure 1 diagrams the relationship of the goal and the following sets of questions and metrics.

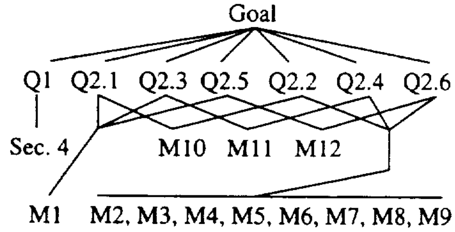

Figure 1: Goal, questions, and metrics

Q1: What are the characteristics of the software systems, the environment, the processes followed, and the personnel? Answers are given in Section 4.

Q2.1/2.2: Is the vertical/horizontal design complexity of modules affected by changes with high *isolation effort* greater than modules affected by changes with low effort?

Q2.3/2.4: Is the vertical/horizontal design complexity of modules affected by changes with high *implementation effort* greater than modules affected by changes with low effort?

Q2.5/2.6: Is the vertical/horizontal design complexity of modules affected by changes that touched a large *number of modules* greater than modules affected by changes that touched few modules?

Answers to questions Q2.x will be developed using the following design complexity and change effort metrics, which are discussed in detail in Section 3:

M1: The number of specifications a module fulfills, either directly or indirectly.

M2: Number of common blocks used in a module.

M3: Number of global variables visible in a module.

M4: Number of global variables used in a module.

M5: Ratio of used:visible global variables.

M6: Number of potential data bindings in a module.

M7: Number of used data bindings in a module.

M8: Measure of fan-in for a module.

M9: Measure of fan-out for a module.

M10: Isolation effort per module per change.

M11: Implementation effort per module per change.

M12: Number of modules affected by a change.

2.2 Available data

Although we would like to assume that all changes are similar in size, this may not be so for enhancements, which range from trivial to extensive. However, we can assume similarity in the size of changes for error corrections.

Table 1 shows the count of data points from the acceptance test and maintenance phases (error corrections are a subset of all changes). Although our original

	Change types	
Phase	Error Corrections	All Changes
Acceptance test	302	508
Maintenance	17	33

Table 1: Data points according to category

goal was to focus on maintenance changes, the limited data encouraged us to include acceptance-test changes. However, interpretation of that data is difficult owing to the different environments, as discussed in Section 4.

2.3 Analysis and threats to validity

The study tests our hypotheses by checking for relationships between the independent variables concerning software design complexity and the dependent variables concerning change isolation effort, change implementation effort, and number of modules changed. The appropriate statistical approach for univariate analysis is a correlation analysis. As will be explained in Section 3, both the isolation and implementation effort metrics lie on an ordinal scale, so we must use a correlation technique which does not require ratio or interval-scale data. We planned to compute Spearman rank-correlation coefficients with respect to single complexity measures of the modules and the maintainability measures.

Based on the notion that a combination of independent variables might better explain high change effort than only a single variable, we planned to analyze multiple variables in combination using a machine-learning technique called Optimized Set Reduction (OSR) [BTH93, BBH93]. OSR finds patterns in the independent (explanatory) variables which reliably predict values of a single dependent variable. The OSR approach is insensitive to the scale of the data, but requires a large data set, ideally several hundred points. We planned to apply the OSR technique to the full data vectors; i.e., consider all explanatory variables together.

If we can find strong correlations between design complexity values and change effort values, or can find patterns of large design complexity values that reliably predict which modules are expensive to change, we will have confirmed our hypotheses for this data set.

There were at least two threats to internal validity. First, the nature of a case study meant that we were not able to control or even measure the factors that influenced the SEL personnel during their day-to-day activities. Second, individual differences may be responsible for some variation (i.e., noise) in the data.

One significant threat to external validity is the specialization of the software-system design used by the SEL. These results may not be applicable to other FORTRAN systems.

3 Complexity and Maintainability

Curtis refines the concept of software complexity into algorithmic and psychological complexity [Cur80]. Algorithmic (or computational) complexity characterizes the run-time performance of an algorithm. Psychological complexity affects the performance of programmers trying to understand or modify a code module. We measured two aspects of psychological complexity, namely the vertical design complexity (the relationship between specifications and modules) and the horizontal design complexity (the relationship between modules). A module is a file with a single subroutine. These relationships are illustrated in Figure 2.

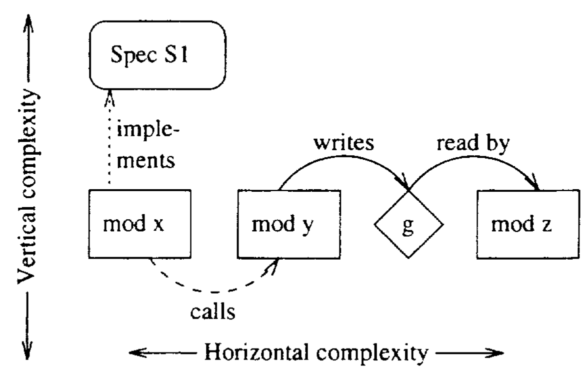

Figure 2: Vertical and horizontal design complexity

3.1 Vertical complexity: the relationship between specifications and modules

The vertical complexity of a module x is the number of specifications the module helps implement. To measure vertical complexity, we count how many specifications a module implements directly (mentioned in the documentation) or indirectly (invoked by another module that implements the specification directly or indirectly). An example is shown in Figure 2, where module x helps implement specification S1 directly and calls module y, meaning that module y helps implement S1 indirectly.

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3.2 Horizontal complexity: the relationship between modules

The horizontal complexity of a module x is characterized by the number of connections between that module and other modules. An example is shown in Figure 2, where module y writes data into a global variable g, that is read in turn by module z. We analyzed the source code to gather data for the following metrics:

- Number of *COMMON blocks* which are referenced in a module.
- Number of *visible global variables*; i.e., the variables defined in the referenced COMMON blocks.
- Number of *used global variables*; i.e., the visible global variables that were also used in the code.
- *Ratio* of used global variables to visible global variables.
- For modules p and q, and a variable x within the static scope of both p and q, a *potential data binding* is defined as an ordered triple (p, q, x) [HB85].
- Again using p, q, and x, a *used data binding* is a potential data binding where p and q either read a value from or assign a value to x [HB85].
- The *fan-in* measure of a module is the number of other modules which call the module.
- The *fan-out* measure of a module is the number of other modules which the module calls.

3.3 Maintainability

Maintainability is an abstract concept that cannot be assessed directly but may be defined using attributes of the software that can be measured. We use change effort as our metric for maintainability.

Changes. The SEL distinguishes between three types of changes. An *error correction* repairs faults in the software. An *enhancement* implements changes for extended specifications. An *adaptation* makes provisions for alterations in the system's environment. For us, the error corrections were of primary interest.

Effort data. The analyses presented here are based on a four-step model of the change activity that guides data collection. In step one. the developers/maintainers become aware of the need for a change. Step two involves isolating the modules to be changed. In step three, they plan and implement the change. Finally, in step four they test the changed code. The change effort data that was available to us were limited to the following, routinely collected items [Nat91b]:

- Isolation effort: the effort to determine which modules must be changed (step two).
- Implementation effort: the effort to plan, implement, and test the change (steps three and four)
- Locality: the number of components affected by a change.

Effort expended during the maintenance phase is collected as a point on an ordinal scale, namely "less than one hour," "one hour to one day," "one day to one week," "one week to one month," and "greater than one month." Effort expended during the acceptance test phase is collected using the ordinal scale of "less than one hour," "one hour to one day," "one day to three days," and "more than three days."

4 Context of the Study

The study was conducted on two projects developed by the Flight Dynamics Division (FDD) of NASA's Goddard Space Flight Center. Data about the FDD's projects are gathered by the Software Engineering Laboratory (SEL), a cooperative effort of NASA's FDD, Computer Sciences Corporation, and the University of Maryland. The SEL was founded and began collecting data about the FDD's development activities in 1976. Data collection from maintenance activities began in 1988 [RUV92].

4.1 FDD Staff

The staff who performed the changes were familiar with both the application domain (ground-support software for satellites), which were similar for both systems, and the solution domain (FORTRAN), which was identical for both systems.

4.2 Activities in the acceptance test phase

During the acceptance test phase, the original developers exercise the system to detect failures and repair faults as needed [Nat91a]. Enhancements and adaptations may also be made to the software during this phase owing to new requirements.

4.3 Activities in the maintenance phase

During the maintenance phase, a team of software engineers who were not the original developers tests the software using simulators and modifies the systems as needed [Nat91a]. These engineers are experts in their application domain, but not necessarily highly familiar with the software systems. The maintenance phase essentially ends when satellites are launched; in any case, no data are collected following the launch.

4.4 The software systems

Project 1 and Project 2 (names have been changed) are ground-support software systems that were coded in FORTRAN. Both were single-mission systems.[1] Their sizes were approximately 130 and 180 KSLOC (carriage returns). These systems determine the exact position of a satellite with respect to other planetary bodies using data sent by the satellite. The systems do not run continuously, they are not subject to real-time constraints, and they are not required to meet highly stringent reliability requirements. For both projects, the software architecture and document standards are highly similar and specific to the FDD environment.

4.4.1 Specifics of Project 1

Project 1 consists of 582 modules. Of those, 23 modules are assembler modules, with a range of 6–3100 SLOC (carriage returns). The other 559 modules are FORTRAN modules (range 2–3200 SLOC). The system consists of 15 subsystems.

Changes in acceptance test. The developers processed 179 change requests during acceptance testing. Those change requests directly affected 163 unique modules, but owing to multiple changes to the same modules, there were 306 changes to code modules. Of the 163 changed modules, 32 modules were not available to us, or were assembler modules that were not analyzed. Therefore 48 changes to individual modules and 33 change requests total could not be analyzed.

Project 1 was in development (design, code, and test activities) for approximately 28 calendar months. Of those 28 months, the acceptance test phase lasted approximately 5 months.

Changes in maintenance. The single maintainer processed 15 change requests during maintenance. Of those, 5 were corrections, 9 were enhancements and 1 was an adaptation. Those change requests directly affected 28 unique modules, but because of multiple changes to the same modules, there were 37 changes to code modules. The assembler modules were not considered (5 change requests, 2 modules).

The maintenance phase for Project 1 began in 1988. Because of launch delays, it lasted about 33 months. The level of effort was extremely low for much of that time.

4.4.2 Specifics of Project 2

Project 2 consists of 816 modules. Of those, 31 modules are assembler modules (range 6–7300 SLOC). In addition to the 747 FORTRAN modules (range 3–2800 SLOC), there are 38 data files (range 9–400 SLOC). The system consists of 30 subsystems.

Changes in acceptance test. The developers processed 413 change requests during acceptance testing. Those change requests directly affected 346 unique modules, but because of multiple changes to the same modules, there were 850 changes to code modules. Of the 346 changed modules, 119 modules were not available to us, or were assembler modules which were not analyzed. Therefore 238 changes to individual modules and 136 change requests total could not be analyzed.

Project 2 was also in development for approximately 28 calendar months. Of those 28 months, the acceptance test phase lasted approximately 7 months.

Changes in maintenance. The four maintainers processed 25 change requests during maintenance. Of those, 12 were corrections, 12 were enhancements, and 1 was an adaptation. Those change requests directly

[1] A single-mission system is expected to cost 2% of development costs per year in maintenance until it is taken out of service, while a multi-mission system is expected to cost 10% [PS93].

affected 55 unique modules, but because of multiple changes to the same modules, there were 67 changes to code modules. Fortunately for our analysis, the assembler modules were not changed.

The maintenance phase for Project 2 began in 1988 and lasted about 19 months.

5 Results

After discussing some problems with the data, we present results from analyzing the maintenance and acceptance test data and sketch results from related work.

5.1 Data difficulties

We encountered some difficulties while trying to collect the data for the metrics defined in Section 2. In all fairness to the SEL, their data-collection forms were not designed to support such a detailed investigation, and we could not change data collection after the fact, so some problems were to be expected.

First, collecting data for metric M1 depended both on the modularity of the specification and the traceability of the specification to the code. At one extreme of modularity, the whole project can be seen as one single specification, while at the other extreme, every condition such as "x > 0" can be also seen as a specification. We began by using the system description document, in which a system is divided into 40–70 subspecifications. Even with this coarse level of modularity, it was not possible to map the modules to the subspecifications with any hope of accuracy because there was no document containing this information. We resolved this difficulty by simplifying the problem. Because the subsystems (Projects 1 and 2 had 15 and 30, respectively) were easily identifiable both in the requirements document and in the code, we essentially labeled each subsystem a "specification." Then we traced modules back to subsystems by analyzing the calling structure of the code.

The change effort data presented a second problem. In the SEL environment, a change activity occurs in response to a change request, and may affect many modules. The effort data are collected for each change activity, but no data for the change effort *per module* are collected. Because it is impossible to determine from the data how much change effort was expended on individual modules, we could not obtain values for metrics M10, M11, and M12 as originally planned. We resolved this difficulty by using an average for each change, namely the average of the complexity measures that were collected from the modules affected by that change. All analyses therefore are focused on *changes* rather than modules. However, by averaging, we reduced the range in complexity values, possibly losing significant differences.

Finally, we concluded that significant differences in effort were hidden by the ordinal scale of the effort data. For example, a maintenance change that required 9 hours of implementation effort is quite different from one that required 39 hours, but both are classified identically as "one day to one week."

5.2 Results from the maintenance data

5.2.1 Vertical complexity measures

First we tested hypothesis 1 using maintenance data, subject to the caveats discussed in Section 5.1.

Data collection process. We built a prototype tool that extracted the module calling trees from the FORTRAN code for each subsystem. This information told us which modules were part of a particular subsystem. While collecting these data, we found that not all of the modules changed are executable modules, and therefore are not in the call tree. Measures of change effort were obtained by querying the SEL database [Nat90] and by examining the data-collection forms completed by the maintainers after making the changes.

Results from univariate analyses. For Project 1, 19 modules that were changed were found in the call tree. Of those 19 executable modules, only 3 supported multiple subsystems; i.e., helped implement more than one specification. For Project 2, 32 modules that were changed were found in the call tree. Of those 32 executable modules, only 1 supported multiple subsystems. This left us with 4 data points for changed modules which supported multiple subsystems. None of the 4 modules participated in changes with above-average isolation or implementation effort.

Results from multivariate analyses. The OSR technique requires a large set of data to be effective. Because the maintenance data set was too small to be used, we have no multivariate results.

Interpretation. We could not support hypothesis 1; the answer to questions 2.1, 2.3, and 2.5 was "not for these data." Although our analysis found many modules that supported more than one subsystem, few of those modules were changed. We later learned that many of the modules which are widely reused are utility functions or so-called "institutional software." This term refers to modules that are reused repeatedly from project to project and are rarely changed.

We also learned that subsystems are designed mostly in isolation from one another, with the result that modules are not reused widely across subsystems. Although our definition of a "specification" was arguably too coarse, we could not refine the traceability further without a detailed familiarity with the systems.

An interesting result was that for Project 1, 12 of the 19 changed executable modules were from a single subsystem. No comparable, frequently changed subsystem was identified in Project 2, although the changes were clustered in 5 of the 30 subsystems.

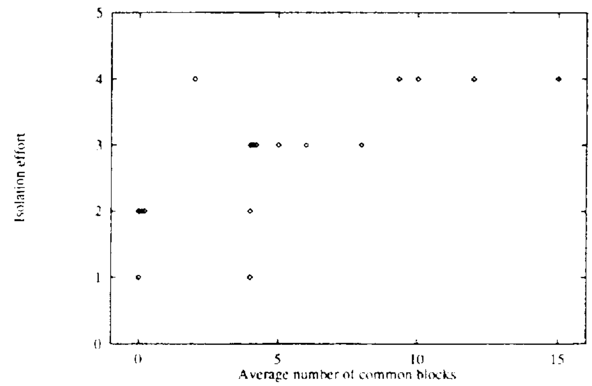

Figure 3: Data for error corrections in maintenance

5.2.2 Horizontal complexity measures

Next we tested hypothesis 2 using maintenance data.

Data collection process. We built a prototype tool which counted the use of common blocks and common-block variables in the FORTRAN code, and reused the calling-tree information from the analysis of vertical complexity for the measures of fan-in and fan-out. After loading all the resulting data into a database system, it computed the necessary complexity values. Recall that module complexity values were averaged on a *per change* basis as explained in Section 5.1. Effort data were obtained as discussed in Section 5.2.1.

Results from univariate analyses. Figure 3 uses data about error corrections from the maintenance phase to plot isolation effort against the average number of used common blocks (metric M2) in the modules affected by each change. This figure shows a trend towards higher effort when the average number of common blocks is also high. Thus encouraged, we computed correlations for the change data from the maintenance phase.

Table 2 shows the Spearman rank-correlation coefficient values for the relationships between all independent and dependent variables for *all changes* during maintenance; Table 3 shows only the coefficient values for *error corrections*. The correlations were computed as explained in Section 2.3. An approximation of the .05 cutoff (a 5% chance of obtaining the numbers by chance) is given in both tables to help judge the significance of the results.

Results from multivariate analyses. As mentioned previously, we had too few data points to apply OSR to the maintenance data.

Interpretation. When considering all changes during maintenance, all measures of global variables correlated positively (some significantly) with isolation effort. The counts of used globals and actual data bindings showed the most significant correlation of all measures; in an absolute sense the correlation is weak (approximately 0.60). These results support the idea that global variables make a program difficult to understand, although this conjecture was not supported by [LZ84] (see also Section 5.4). We found no significant correlation between complexity measures and implementation effort, nor between complexity measures and the number of modules changed. The measures of control-flow complexity were not helpful. To summarize the results for all changes, we can support hypothesis 2 in some respects; the answer to question 2.2 (isolation effort) is a qualified yes for some of the measures, but the answer to questions 2.4 (implementation effort) and 2.6 (locality) is "not for these data."

When considering just the error corrections during maintenance, the measures of global variables correlate positively and much more strongly with the isolation effort than previously. Both the counts of used globals

Dependent variables (averages per change)	Independent variables Isolation effort	Implem'n effort	Modules changed
M2: Common blocks	**.415**	.088	-.376
M3: Visible global vars	**.575**	.207	-.303
M4: Used globals vars	**.628**	.228	-.198
M5: Ratio used:visible globals	**.534**	.303	.105
M6: Potential data bindings	**.528**	.193	-.330
M7: Used data bindings	**.599**	.214	-.294
M8: Fan-in	-.268	-.010	.067
M9: Fan-out	.322	.181	-.363

N = 33, critical r (.05) t approximation = .343

Table 2: Spearman rank-correlation coefficients for *all changes* during *maintenance*

Dependent variables (averages per change)	Independent variables Isolation effort	Implem'n effort	Modules changed
M2: Common blocks	**.738**	.403	-.169
M3: Visible global vars	**.785**	**.511**	-.143
M4: Used global vars	**.799**	**.511**	.000
M5: Ratio used:visible globals	**.619**	**.493**	.164
M6: Potential data bindings	**.770**	**.511**	-.214
M7: Used data bindings	**.813**	**.511**	-.102
M8: Fan-in	-.406	-.208	-.096
M9: Fan-out	**.610**	**.545**	-.143

N = 17, critical r (.05) t approximation = .482

Table 3: Spearman rank-correlation coefficients for *error corrections* during *maintenance*

and actual data bindings again showed the most significant correlations, in this case fairly strong in an absolute sense (approximately 0.80). We also found correlations with implementation effort; some were significant but again weak in an absolute sense (approximately 0.50). Fan-out correlated positively weakly with both measures of effort. No measures correlated with the number of affected modules. To summarize the results for the error corrections, we can support hypothesis 2 strongly; the answers to questions 2.2, 2.4, and 2.6 are a reasonable yes, a weak yes, and another "not for these data."

Finally, we found it interesting that the number of changed modules frequently correlated *negatively*, although weakly, with the complexity values. We are unable to explain this result.

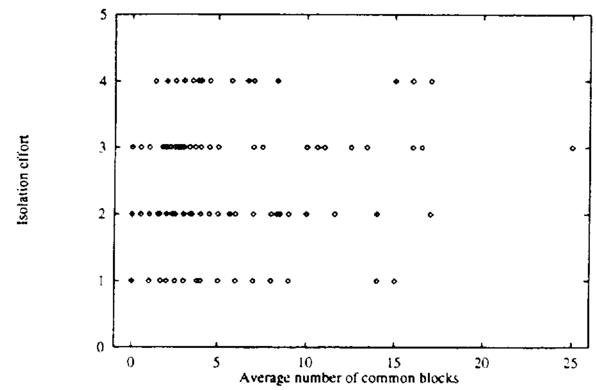

Figure 4: Data for error corrections in acceptance test

5.3 Results from the acceptance test data

As mentioned earlier, we extended the scope of the study to include data from the acceptance test phase. The results must be interpreted carefully, because the measures of the source code were computed using the code as it existed at the end of the maintenance phase. A version of the code from the end of the acceptance test phase was not available.

5.3.1 Vertical complexity measures

Due to the problems discussed in Sections 5.1 and 5.2.1, we did not test hypothesis 1 using acceptance test data.

5.3.2 Horizontal complexity measures

Finally, we tested hypothesis 2 using the acceptance test data.

Data collection process. The measures M2 to M9 were computed from the source code as of the end of the maintenance phase. Again, module complexity values were averaged on a *per change* basis as explained in Section 5.1. Measures of change effort were obtained by querying the SEL database [Nat90].

Results of univariate analyses. Figure 4 uses data about error corrections from the acceptance test phase to plot the isolation effort against the average number of common blocks in the modules affected by each change. Plots of isolation and implementation effort against other independent variables were similarly random, which discouraged us from computing univariate correlations.

Results of multivariate analyses. Because we had data for several hundred changes in the acceptance test phase, we were able to apply the OSR technique [BTH93, BBH93]. Based on the results achieved when working with the maintenance data, we restricted the data set to the error corrections. All analyses took the approach of trying to identify whether the error corrections (changes) would be inexpensive or expensive, where inexpensive was defined as requiring one day or less (the lower two values on the ordinal scale) and expensive was defined as requiring more than one day (the upper two values). The technique found reliable patterns when using isolation effort as the dependent variable, but found no reliable results when using implementation effort or locality as the dependent variable.

All results are expressed as OSR patterns. Patterns provide interpretable models where the impact of each predicate can be easily evaluated [BTH93]. An OSR pattern is a set of one or more predicates, where predicates have the form ($EV_i \in EVclass_{ij}$), meaning that a particular explanatory (independent) variable EV_i belongs to part of its value domain, i.e., $EVclass_{ij}$. Taken as a whole, the pattern predicts whether the value of the dependent variable will be in the high-cost or the low-cost class. For each pattern, we state the reliability of the prediction (a measure of pattern accuracy), and the significance level of the reliability (whether the pattern is based on a sufficiently large set of data to be trusted). The OSR technique found reliable and significant patterns which predict low and high isolation effort. We present patterns which had high reliability values (> 0.8) and low reliability significance values (< 0.05).

Pattern L1:
Fan-in ∈ 26-100% AND
fan-out ∈ 0-50% ⇒ low
(reliability 0.85, rel. sig. 0.011)

Pattern L1 suggests that modules with medium to high fan-in values and low fan-out values were easy to change (predicts low isolation effort). This pattern may indicate leaf modules (such as library subroutines) which are called frequently but call few other modules.

Pattern L2:
Used var ∈ 0-12% OR
used db ∈ 0-11% ⇒ low
(reliability 0.92, rel. sig. 0.001)

Pattern L2 suggests that modules with low numbers of used variables or low numbers of used data bindings were easy to change (predicts low isolation effort).

Pattern H1:
Fan-in ∈ 8-26% AND
(used db ∈ 20-100% OR
used var ∈ 20-100%) ⇒ high
(reliability 1.00, rel. sig. 0.000)

Pattern H1 suggests that if a module is called by a relatively low number of other modules, and additionally has many used data bindings or many used variables, then that module was expensive to change (predicts high isolation effort).

Pattern H2:
Ratio used:visible ∈ 63-100% AND
(vis var ∈ 34-100% OR
used db ∈ 30-100%) ⇒ high
(reliability 1.00, rel. sig. 0.001)

Pattern H2 suggests that if a module has a high ratio of used to visible global variables, and additionally has many visible variables or many used data bindings, then that module was expensive to change (predicts high isolation effort).

Pattern H3:
Fan-out ∈ 42–100%
AND used db ∈ 59-100% ⇒ high
(reliability 1.00, rel. sig. 0.007)

Pattern H3 suggests that modules which call many other modules and have many data bindings to other modules were expensive to change (predicts high isolation effort).

Interpretation. The univariate analyses were not helpful, but the OSR analysis identified some patterns that reliably characterize modules which participated in error corrections with both low and high isolation effort. All of the patterns support hypothesis 2. We have not established a causal relationship between the patterns and isolation effort, no statistical analysis technique does so, but we have identified a set of patterns that may be suitable for further investigation.

5.4 Results from related studies

We summarize the results of previous studies and experiments that analyzed the effects of design complexity on various dependent variables. Note that comparisons with related work are dangerous owing to different definitions of both independent and dependent variables.

Lohse and Zweben [LZ84] ran a controlled experiment to examine the effects of data coupling (data flow among modules) via global variables versus formal parameters, in the context of performing maintenance changes (enhancements) to two software systems. The primary dependent variable was the time required to implement the enhancement. They found no significant differences attributable to the use of global variables versus formal parameters.

Card et al. [CCA86] performed a case study on five SEL FORTRAN systems to examine the impact of various design practices on the dependent variables fault rate and cost in the context of development. They found no correlation with the percentage of referenced variables in COMMON blocks but a positive correlation with the number of descendants (fan-out). The percentage of unreferenced variables from COMMON blocks correlated with faults, but not with cost.

Rombach [Rom87] ran a controlled experiment to examine the effects of various programming-language constructs on isolation effort, implementation effort, and locality in the context of performing maintenance changes (enhancements) to two software systems. Complexity was measured in terms of information flow, which includes both data bindings and control flow between modules. He found a correlation of both isolation effort and locality with external complexity, but no correlation of implementation effort with external complexity. Our results support his with respect to isolation and implementation effort, but not locality.

Card and Agresti [CA88] performed a case study on SEL FORTRAN systems to test for a relationship between a combined complexity measure and either productivity (lines of code delivered per unit of time) or fault rate in the context of development. Their combined measure of local complexity (e.g., cyclomatic complexity) and structural complexity (e.g., module fan-out) correlated well with productivity and number of faults. Because their study does not separate local (internal) complexity from structural (external) complexity, we cannot compare results.

6 Conclusion and Lessons Learned

The data from the two SEL systems support our hypothesis 2, so we can answer in the affirmative that horizontal design complexity appears to affect maintenance effort (isolation effort for error corrections). However, we have only demonstrated a possible relationship. We cannot establish causation using a case study.

Next we summarize the results of the study in terms of what the SEL can learn, what we learned, and what the software-engineering community can learn. Our analyses, which we primarily see as pointers for further investigation, found a number of relationships between software design complexity and maintenance effort that might help the SEL predict maintenance effort. Univariate analysis showed that the metrics "used globals" and "used data bindings" correlated strongly with the isolation effort for error corrections performed during the maintenance phase. Data for other metrics relating to the definition and use of global variables also correlated with isolation effort, but much less strongly with implementation effort. The measure of fan-out was also somewhat helpful in explaining high isolation effort. Multivariate analysis of acceptance test data using OSR found a number of patterns which were strong indicators of both low and high isolation effort in this data set. Future studies could be performed using other SEL systems to test whether the relationships and patterns which we found hold for more than just the two systems that we analyzed.

We gained a better understanding of the data required for thoroughly testing our hypotheses. First, to measure vertical complexity, both the modularity of the specification and its traceability to the code must be addressed. To solve the latter problem, a traceability matrix could be constructed in which the rows represent individual code modules and the columns represent units of the specification. A mark in the matrix means that the module of that row implements the unit of specification of that column. To build such a matrix, the modularity of the specification is critical, but beyond the scope of this paper. Second, to measure the effort required for a change, we need to collect the isolation and implementation effort on a per-module basis whenever possible. A minor change to the SEL's data-collection forms could be to collect an estimate of the percentage of the total effort required by each module. However, some effort, such as the effort to test the changed modules together, cannot be allocated to individual modules. Third, the simplest and most helpful change to the SEL's data collection forms (from our point of view) would be the use of a ratio scale such as days or hours for collecting effort data instead of the ordinal scales currently in use. This would allow us to distinguish more precisely between different changes as well as to compare effort data between the maintenance and acceptance test phases.

Finally, we believe that an empirical investigation such as this one uncovers more challenging questions than it answers. Future work might include replicating our study by analyzing the designs of other SEL software systems or systems from other software development organizations. Our data might also be used as a basis for planning and running a controlled experiment such as the one discussed in [Rom87] to test our hypotheses more rigorously. In a controlled experiment, programmers (subjects) might implement changes of similar sizes in modules that have low, medium, and high software design complexities. This would allow the researchers to control for many effects as well as to measure the effort required on a per-module basis to implement changes. Such an experiment would offer stronger evidence for refuting or accepting our hypotheses than any case study.

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Does Software Design Complexity Affect Maintenance Effort?

A study of existing NASA/SEL data

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STTI-KL

Overview

- Problem and hypotheses
- Vertical and horizontal design complexity
- Study design, independent and dependent variables
- Results for maintenance data
- Results for acceptance test data
- Conclusions and lessons learned

Problem and hypotheses

It is generally believed that software design complexity affects error rate, change effort etc.

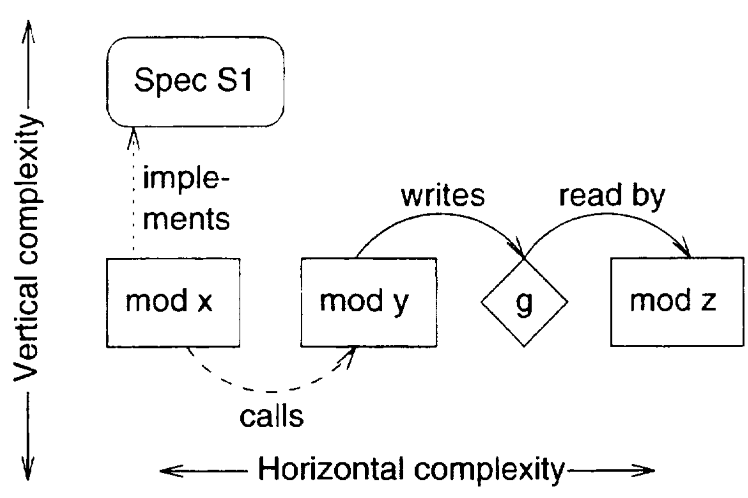
Supporting studies include: Card et al., TSE 86; Rombach, TSE 87; Card & Agresti, JSS 88; Briand et al., CSM 93.

We used existing SEL data to test two related hypotheses:

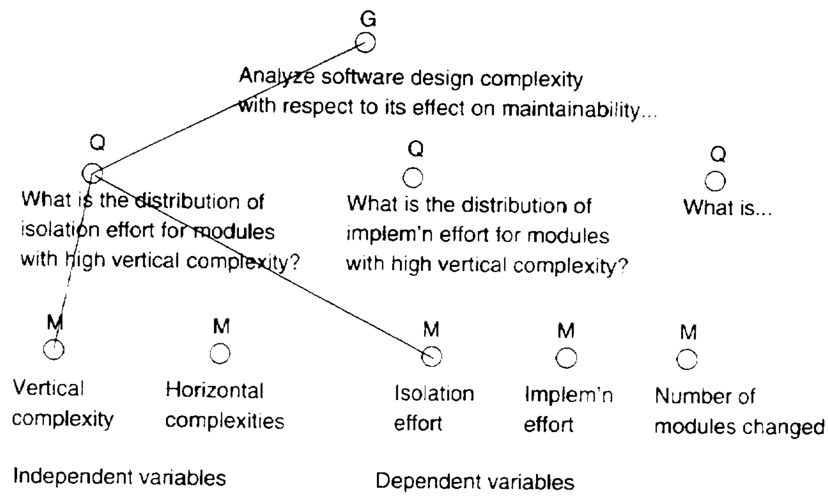
Hypothesis 1: Module implements many specifications (vertical complexity) $\Rightarrow$ maintenance effort will be high

Hypothesis 2: Module is tightly coupled to others (horizontal complexity) $\Rightarrow$ maintenance effort will be high

Terminology: Design complexity



Design via G/Q/M



STTI-KL 4/9

Design: variables

- Independent variables (newly gathered):
  - Vertical design complexity (1 measure)
    - Number of specifications which a module implements (in)directly
    - Problems: modularity of the specification and traceability to code
  - Horizontal design complexity (8 measures)
    - Number of COMMON blocks referenced in a module, ...
    - Minor problem: limited to static metrics derived from the code

- Dependent variables (existing data):
  - Maintainability (3 measures)
    - Isolation effort, Implementation effort, Number of modules changed
    - Problems: collected per change, not per module; ordinal scale for effort

STTI-KL 5/9

Results for error corrections in maintenance

Unable to test hypothesis 1 (vertical complexity).

Results for hypothesis 2 (horizontal complexity) using 17 data points:

- Significant and strong correlations found with isolation effort

  Example: 0.785 for count of visible global variables (.05 cutoff: .482)

- Significant but weak correlations found with implementation effort

  Example: 0.511 for count of visible global variables (.05 cutoff: .482)

- No significant correlations found with locality

  Example: -.303 for count of visible global variables (.05 cutoff: .482)

STTI-KL 6/9

Results for error corrections in acceptance test

Unable to test hypothesis 1 (vertical complexity).

Results for hypothesis 2 (horizontal complexity) using 302 data points:

- Analyzed variables in combination using Optimized Set Reduction (OSR)

- Found reliable patterns for complexity values which predict isolation effort:
  - Fan-in in 26-100% of value range AND fan-out in 0-50% ⇒ low iso. eff. (Reliability 0.85, reliability significance 0.011)
  - Fan-out in 42-100% AND used data bindings in 59-100% ⇒ high iso. eff. (Reliability 1.00, reliability significance 0.007)

STTI-KL 7/9

Related work

Lohse & Zweben 1984 (JSS):
Controlled experiment to compare coupling via globals vs. formal parameters.
Results showed no significant difference; is not directly comparable.

Card et al. 1986 (TSE):
Case study of influence of software design practices on cost and fault rate.
Fan-out was highly influential; the influence was not as large in our study.

Rombach 1987 (TSE):
Controlled experiment to analyze influence of complexity on maint. effort.
Isolation effort affected more than impl'n effort; supported by our study.

Card & Agresti 1988 (JSS):
Case study of influence of complexity on productivity and fault rate.
Different definition of complexity makes comparison impossible.

Conclusions and lessons learned

- Cannot test Hypothesis 1 (vertical complexity) using existing SEL data.
- Can support Hypothesis 2 (horizontal complexity) using existing SEL data:
  - Univariate analysis of horizontal complexity measures (i.e., coupling) identified modules that are likely to cause changes to be expensive.
  - OSR identified patterns in complexity (coupling) data likely to increase isolation effort, but found no reliable patterns for implementation effort.
- Lessons for the SEL:
  - Correlations and patterns help predict maintenance effort.
  - We are not confident enough to recommend complexity (coupling) limits.
  - Need effort data drawn from a ratio scale ("days").